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# Time-varying correlation between islamic stock indices: evidence from the GCC countries based on MGARCH-DCC approach

Mona Yousef[1] and Mansur Masih[2]

**Abstract**

The paper makes an attempt to investigate the portfolio diversification opportunities available within the Islamic stock indices in the GCC countries. That requires the estimation of the time-varying variances of and covariances between the daily returns of the GCC Islamic stock indices. Hence the method used is the recent multivariate GARCH-DCC which takes care of their time-varying relationships. The findings tend to indicate that the unconditional volatility of the GCC stock returns are very low which may indicate that the reruns are stable and the risk is very low. However, the VaR estimator shows that the risk was rising dramatically since 2011, probably due to the political instability during this period. The time-varying conditional correlation between the stock returns of these countries appears to be low in general which provides an advantage to the investors interested in investing in the GCC financial markets. That means it provides more stable returns with low correlation between the stock returns and thus less risky. The results also indicate lower level of integration between the GCC stock markets.

**Keywords**: Islamic stock indices, GCC, time-varying correlation, MGARCH-DCC

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## Introduction: the objectives motivating the study

A major issue facing the investors in the contemporary financial world is how to minimize risk while investing in a portfolio of assets. An understanding of how volatilities of and correlations between asset returns change over time including their directions (positive or negative) and size (stronger or weaker) is of crucial importance for both the domestic and international investors with a view to diversifying their portfolios for hedging against unforeseen risks as well as for dynamic option pricing.

This paper makes an attempt to investigate the portfolio diversification opportunities available within the Islamic stock indices in the GCC countries. With that end in view, we need to estimate the extent of variances of and covariances between the returns of stocks. The unconditional estimates have got a major limitation in that they assume constancy of the variances and covariances during the time period under review. However, in the real world, the variances and covariances are not constant but are time-varying. For that we need to employ a method that takes care of their dynamic time-varying relationship. Hence the appropriate method to take care of the time-varying relationship between the volatilities of the stock returns is the recent multivariate GARCH -DCC method that we intend to use in the case of the GCC countries which have remained relatively less explored.

## Data and Methodology: MGARCH -DCC

The dataset used in this study consist of daily observations of the Standard & Poor's (S&P) Emerging Market Indexes for Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE) for the period starting February 02, 2004. All stock markets indexes prices are in each country's local currency terms and are based on the closing price of the day. The database time-series are drawn from the DataStream.

In a multivariate GARCH (p, q) model, conditional variance and covariance of each asset depend upon not only on its own past conditional variance and past squared innovations but also on the past squared innovations and past conditional variances of the other assets (Bollerslev et al. 1994). The multivariate GARCH model can be used to estimate the Dynamic Conditional Correlations (DCC) for a portfolio composed of asset returns. The dynamic conditional correlations (DCC) enable a determination of whether the shocks to the volatilities in asset returns such as, the forward and futures returns of various maturities are substitutes or complements in terms of taking risk.

The main merit of Dynamic Conditional Correlations (DCC) in relation to other time-varying estimating methods ( such as, rolling regressions and Kalman filters and their variants such as, Flexible Least squares ) is that it accounts for changes in both the *mean* and *variances* of the time series (unlike the above methods which account for only the time-varying changes in the *mean*). In other words, DCC allows for changes both in the first moment (mean) and the second moment (variance). Understanding how correlations and volatility change over time and when they would be strong or weak is a persuasive motivation for the use of DCC models particularly in the financial markets. The DCC modeling allows us to pinpoint changes ( both *when* they occur and *how* ) in the interdependence between time series variables.

DCC estimation involves 2 steps:

(i) Univariate volatility parameters are estimated by using GARCH models for each of the variables. So if there are two variables, then two GARCH equations are estimated. Just as an example:

$$h_t = c_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + b_2 h_{t-2} + m_1\varepsilon_{t-1}^2 I_{\varepsilon>0}$$

(GJR, 1993 Asymmetric GARCH equation).

Where $I$ is an indicator function in which it equals 1 when the standardized residuals of the series ($\varepsilon_t$) are positive and equals 0 otherwise. A negative value of 'm' implies that periods with negative residuals would be immediately followed by periods of higher variance compared to the periods of positive residuals. The equation for GARCH is estimated in step 1 (for each variable) to estimate the residual ($\varepsilon_t$).

(ii) The standardized residuals ($\varepsilon_t$) from the first step are used as inputs for estimating a time-varying correlation matrix (by estimating DCC equation parameters).

$$H_t = D_t R_t D_t$$

Here:

$H_t$ : Conditional covariance matrix

$D_t$ : Diagonal matrix of conditional time varying standardized residuals ($\varepsilon_t$) that are obtained from the univariate GARCH models (on-diagonal elements or variance or volatility component)

$R_t$ : Time varying correlation matrix ( off-diagonal elements)

The likelihood of the DCC estimator is written as:

$$L = -0.5 \sum_{t=1}^{T} (k \log(2\pi) + 2 \log(|D_t|) + \log(|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t)$$

(a) In the first step, only the volatility component ($D_t$) is maximized; i.e. the log likelihood is reduced to the sum of the log likelihood of univariate GARCH equations.

(b) In the second step, correlation component ($R_t$) is maximized (conditional on the estimated $D_t$ ) with elements $\varepsilon_t$ from step 1. This step gives the DCC parameters, α and β,

$$R_t = (1 - \alpha - \beta)\,\overline{R} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta R_{t-1} \qquad \text{(DCC equation)}$$

If $\alpha = \beta = 0$[1], then $R_t$ is simply $\overline{R}$ and CCC model is sufficient. The models have GARCH-type dynamics for both the conditional correlations and the conditional variances. The time-varying conditional variances can be interpreted as a measure of uncertainty and thus give us insight into what causes movement in the variance.

The two-step estimation of the likelihood function is consistent, albeit inefficient (Engle and Sheppard, 2001). The DCC allows asymmetries, meaning the weights are different for positive and negative changes to a series. The asymmetries are in the variances (not in the correlations) (Cappiello, Engle and Shephard, 2003).

Conditional correlation is a forecast of the correlation that would be appropriate next period conditional on this period's data. Therefore, the uncertainty in this forecast (assuming correctly specified model) is simply due to only parameter uncertainty.

### The empirical results and discussions:

**Multivariate GARCH with underlying multivariate t-distribution**

Converged after 32 iterations

Based on 1362 observations from 30-Jan-04 to 20-Apr-09.
The underlying multivariate GARCH model is:
bahrain bahrain(-1) c; saudi saudi(-1) c; qatar qatar(-1) c; kuwait kuwait(-1) c; dubai dubai(-1) c; oman oman(-1) c
Volatility decay factors unrestricted, different for each variable.
Correlation decay factors unrestricted, same for all variables.

| Parameter | Estimate | Standard Error | T-Ratio[Prob] |
|---|---|---|---|
| lambda1_BAHRAIN | .44520 | .089444 | 4.9774[.000] |
| lambda1_SAUDI | .84472 | .018015 | 46.8887[.000] |
| lambda1_QATAR | .62721 | .043662 | 14.3651[.000] |
| lambda1_KUWAIT | .56890 | .039736 | 14.3172[.000] |
| lambda1_DUBAI | .74263 | .042384 | 17.5214[.000] |
| lambda1_OMAN | .81093 | .031436 | 25.7963[.000] |

[1] $\beta$ close to 1 indicates a strong degree of persistence in the series for correlations ($R_t$), while ($\alpha + \beta$) close to 1 indicates high persistence in the conditional variance.

| | | | |
|---|---|---|---|
| lambda2_BAHRAIN | .25683 | .036601 | 7.0170[.000] |
| lambda2_SAUDI | .12894 | .013893 | 9.2809[.000] |
| lambda2_QATAR | .28142 | .030652 | 9.1813[.000] |
| lambda2_KUWAIT | .40263 | .036175 | 11.1301[.000] |
| lambda2_DUBAI | .16896 | .023674 | 7.1368[.000] |
| lambda2_OMAN | .11045 | .015923 | 6.9365[.000] |
| delta1 | .99646 | .0011543 | 863.2909[.000] |
| delta2 | .0034199 | .6163E-3 | 5.5490[.000] |
| df | 5.9913 | .28190 | 21.2536[.000] |

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Maximized Log-Likelihood = 31987.9

df is the degrees of freedom of the multivariate t distribution

**Estimated Unconditional Volatility Matrix**

1362 observations used for estimation from 30-Jan-04 to 20-Apr-09

Unconditional Volatilities (Standard Errors) on the Diagonal Elements

Unconditional Correlations on the Off-Diagonal Elements

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| | BAHRAIN | SAUDI | QATAR | KUWAIT | DUBAI | OMAN |
|---|---|---|---|---|---|---|
| BAHRAIN | .0027164 | .088608 | .23881 | .15671 | .24420 | .26283 |
| SAUDI | .088608 | .0092868 | .15418 | .085939 | .23565 | .13828 |
| QATAR | .23881 | .15418 | .0076579 | .11964 | .33223 | .36989 |
| KUWAIT | .15671 | .085939 | .11964 | .010189 | .13529 | .091305 |
| DUBAI | .24420 | .23565 | .33223 | .13529 | .0088536 | .30685 |
| OMAN | .26283 | .13828 | .36989 | .091305 | .30685 | .0056358 |

For the time-varying conditional volatilities and correlations see the Post Estimation Menu.

The upper panel of the above results present the maximum likelihood estimates of $\lambda_{i1}$ and $\lambda_{i2}$ (Volatility Parameters) for the six stock index returns, and $\delta 1$ *and* $\delta 2$ (Mean reverting parameters, $\Phi_1$ and $\Phi_2$).

We observe that all volatility parameters are highly significant, which implies gradual volatility decay i.e. high riskiness of the stocks return gradually decays (dies out) following a shock in the market, which makes the return highly volatile. Even if we add Lamda1 and Lamda2 of the stocks indices in the all countries we find them less than unity, implies that the volatility of the GCC stock returns are not following IGARCH, i.e. the shock to volatility is not permanent.

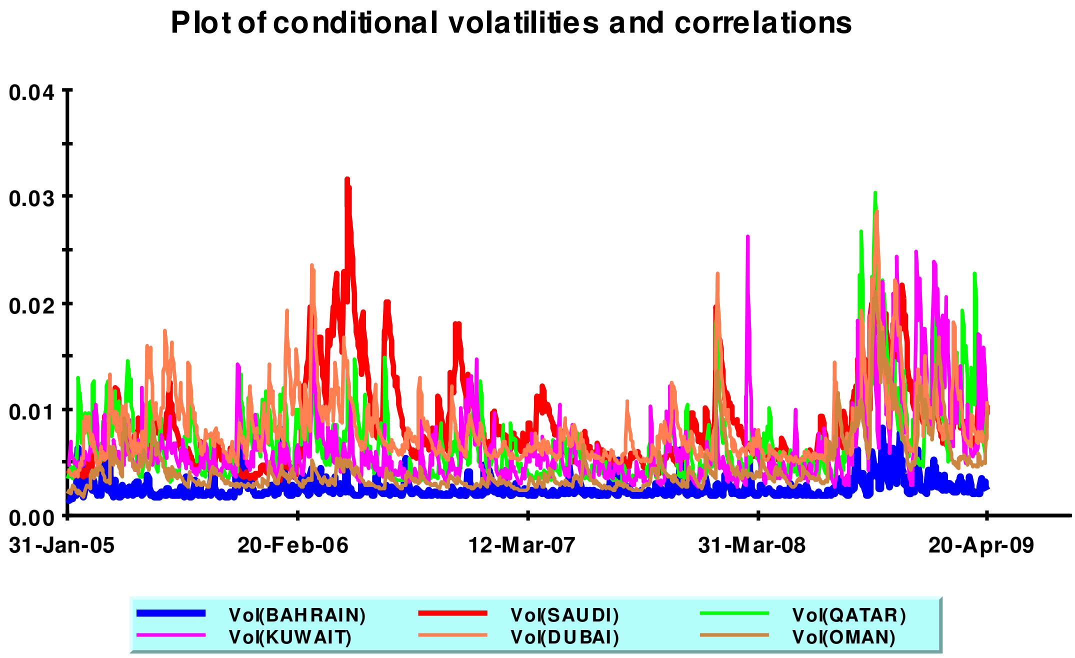
The lower panel of the results reports the estimated unconditional volatilities and unconditional correlation cross correlations between the stocks returns. The off diagonal elements represent unconditional correlation and diagonal elements represent unconditional volatilities of the stocks returns. We can see that unconditional volatility in the all sample is very small. This may indicate that the GCC stock returns are stable. The highest volatility for Kuwait stock return (0.010189) and the lowest for Bahrain stock index return (0.027164), which implies that Bahrain stock return is the most stable return among GCC countries. Regarding the cross return correlation, we observe that the correlation between the GCC stock returns are low in general. The highest correlation between the stock return is between Oman and Qatar (0.36). these results suggest lower level of integration between the GCC stock markets. These results may help investors who are interested in investing in those stock markets on deciding the composition of portfolio that brings the risk to the minimum level using the diversification strategies.

The table below presents the regression results for each equation

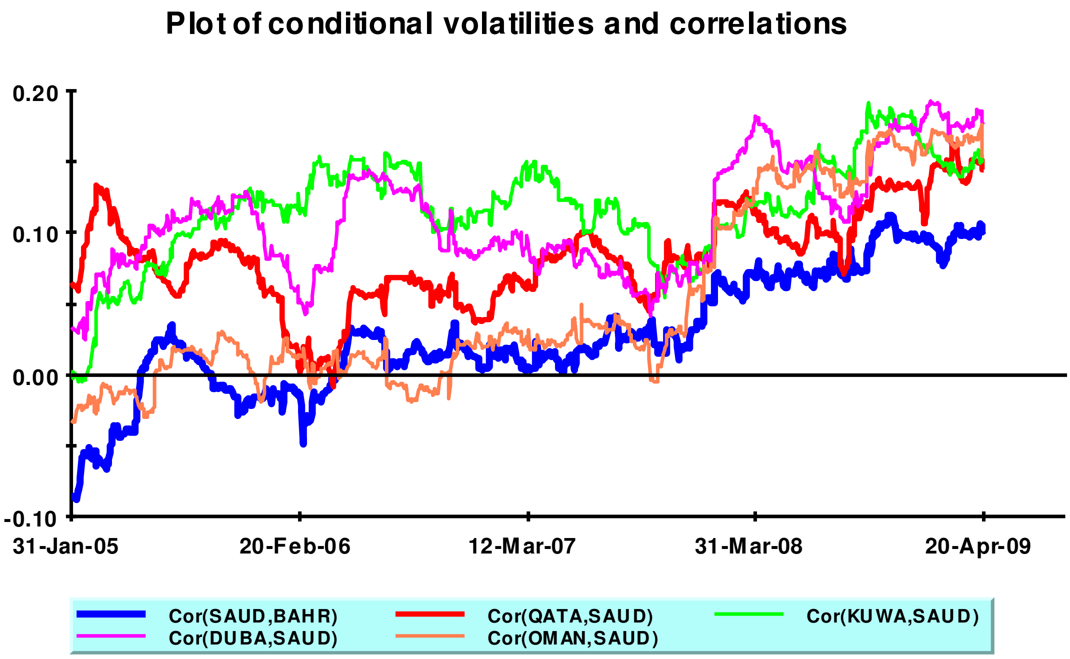
| Regressors | Coefficient | Standard Error | T-Ratio[Prob] |
|---|---|---|---|
| BAHRAIN(-1) | .21678 | .026282 | 8.2482[.000] |
| SAUDI (-1) | .076780 | .026840 | 2.8606[.004] |
| QATAR (-1) | .26625 | .025954 | 10.2584[.000] |
| KUWAIT (-1) | -.29364 | .025733 | -11.4110[.000] |
| DUBAI(-1) | .050370 | .026936 | 1.8700[.062] |
| OMAN(-1) | .20004 | .026432 | 7.5683[.000] |

From the above result, we can see that the estimated parameters for the temporal lag of the variables are different for every equation. It is very small in Dubai and Saudi (0.05, 0.07) respectively and range from 0.20 to 0.29 for the rest and significant at 5% level except in the Dubai case. These results suggest small influence of first lag values on the stock returns.

**Plotting the Estimated Conditional Volatilities and Correlations**




From the above graph, we can observe that the conditional volatilities of all stock returns move more closely together. We can notice that the volatility is very high for all GCC stock returns in 2009 which may reflect the influence of global financial crisis.




From the above graph, we observe that conditional correlations of returns on Saudi stock market with other stock returns have been rising over time. This result suggests that Saudi stock market is a leading variable in order to detect the return movement of other stock market.

**Testing the validity of the t-DCC model:**

**LM test:**

Test of Serial Correlation of Residuals (OLS case)

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Dependent variable is U-Hat

List of variables in OLS regression:

Intercept

522 observations used for estimation from 21-Apr-09 to 20-Apr-11

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| Regressor | Coefficient | Standard Error | T-Ratio[Prob] |
|---|---|---|---|
| OLS RES(-1) | .13659 | .044358 | 3.0793[.002] |
| OLS RES(-2) | .053658 | .044798 | 1.1978[.232] |
| OLS RES(-3) | -.3327E-3 | .044727 | -.0074382[.994] |
| OLS RES(-4) | .0067733 | .044714 | .15148[.880] |
| OLS RES(-5) | .032354 | .044685 | .72405[.469] |
| OLS RES(-6) | .0059300 | .044713 | .13262[.895] |
| OLS RES(-7) | .014055 | .044713 | .31435[.753] |
| OLS RES(-8) | .042906 | .044704 | .95976[.338] |
| OLS RES(-9) | -.034590 | .044760 | -.77279[.440] |
| OLS RES(-10) | .081373 | .044799 | 1.8164[.070] |
| OLS RES(-11) | -.0030708 | .044890 | -.068407[.945] |
| OLS RES(-12) | .028179 | .044483 | .63347[.527] |

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Lagrange Multiplier Statistic    CHSQ(12)=  19.3255[.081]

F Statistic                F(12,509)=   1.6307[.080]

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U-Hat denotes the probability integral transform.

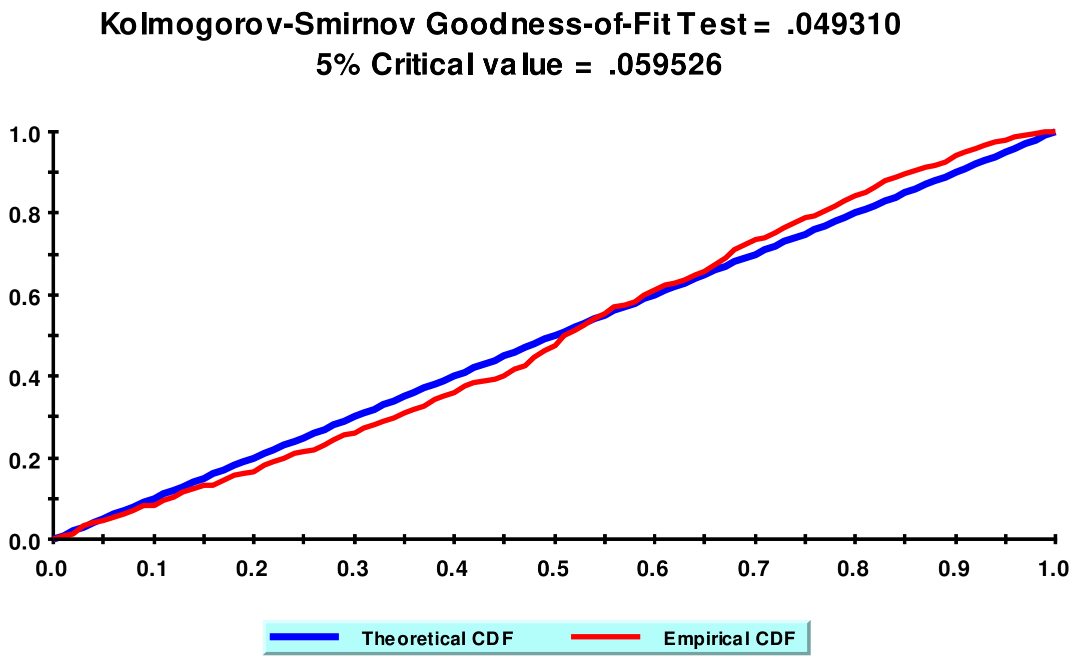
Under the null hypothesis, U-Hat should not display any serial correlation.

Here, Null Hypothesis: H0: t-DCC model is correctly specified

H1: t-DCC model is not correctly specified

The LM test equal to 19.32 (P value = 0.081), which is not statistically significant and we cannot reject our null hypothesis and we conclude that t-DCC model is correctly specified.

KLAMAGROVE



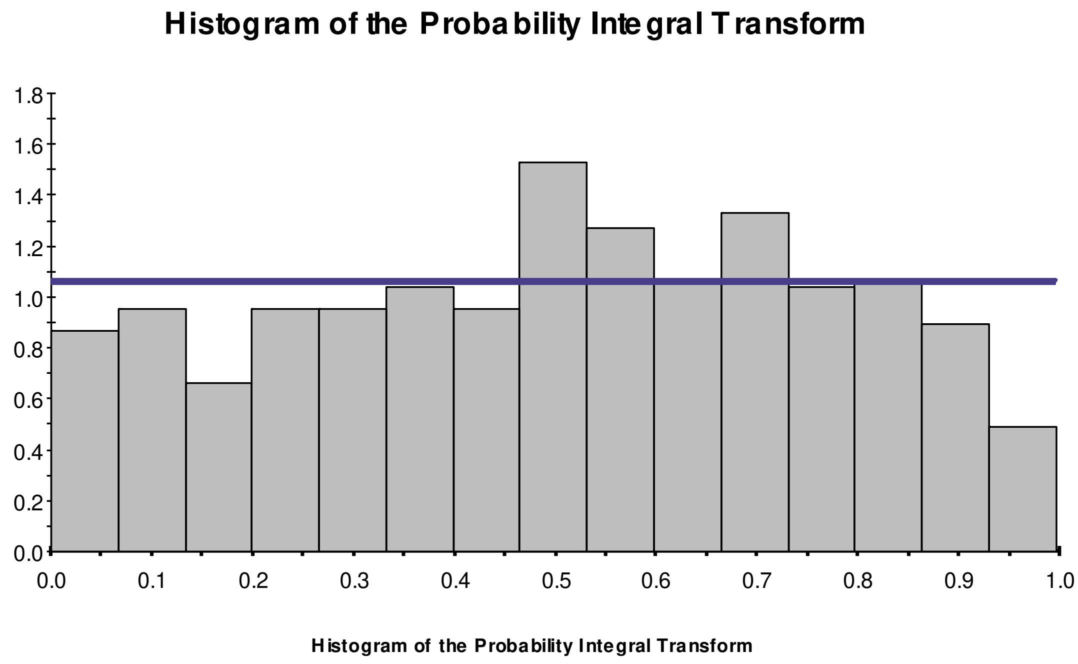

The above graph compares the empirical cumulative distribution function of the probability integral transform variable with that of a uniform.

Null Hypothesis: H0: The probability integral transforms are uniformly distributed.

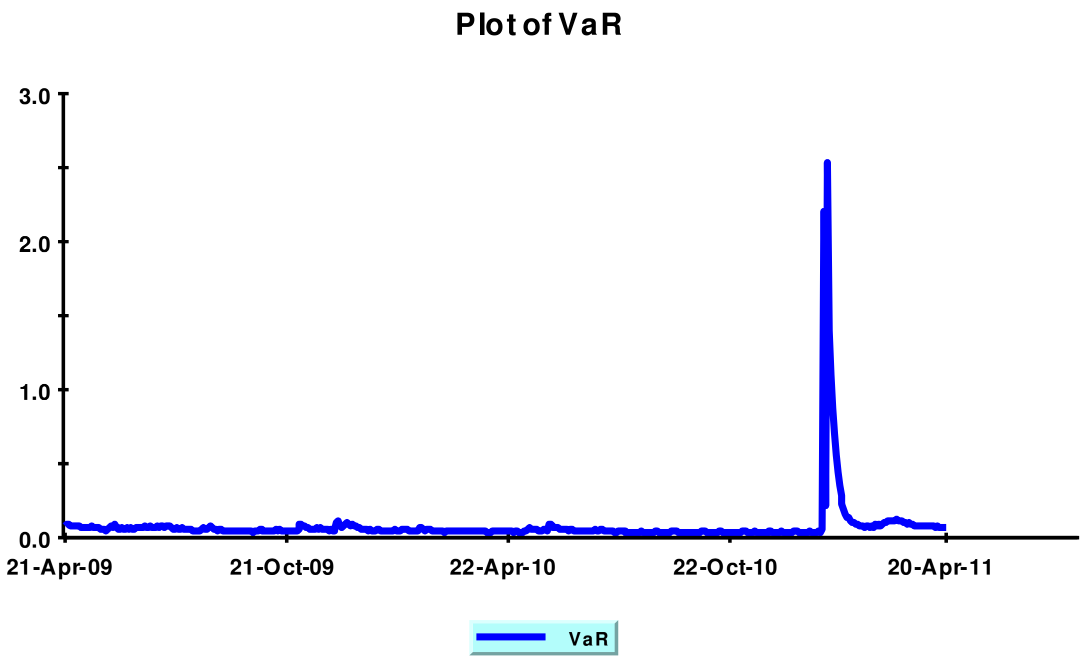
H1: The probability integral transforms are not uniformly distributed

In the above figure, we can see that the Kolmogorov-Smirnov test statistic is 0.049, which is lower than 5% critical value. Therefore, we cannot reject our null hypothesis that the probability integral transforms are uniformly distributed.

**The histograms of the probability integral transform variable:**




**The VaR of the portfolio for the forecasting period:**



The graph shows low level of VaR during the period 2009-2010 however the picture is changing in 2011 the VaR increased dramatically probably due to the political instability during this period.

```
      Mean VaR Exceptions and the Associated Diagnostic Test
Statistics
****************************************************************
***************
 Mean Hit Rate (pihat statistic) =    .99234 with expected value
of    .99000
 Standard Normal Test Statistic=   .53667[.591]
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From the above table, we can see that the mean hit rate (0.99234) is very close to the expected value (0.99000), and the test statistic is not significant. Both tests support the validity of the t-DCC model.

**Concluding remarks**

This paper investigates the relationship between the daily stock returns of the GCC markets for the period starting February, 2 2004. Dynamic unconditional correlation analysis concludes that the volatilities of the GCC stock returns are very low which may indicate that the returns are stable and the risk is very low. However, the VaR estimator shows that the risk is rising dramatically in 2011 probably due to the political instability during this period. On the other hand, the conditional correlations between the stock return of these countries are low in general which provides advantage to the investors interested in investing in the GCC financial markets. That means it provides more stable returns with low correlation between the stock return and thus less risky. The results also indicate lower level of integration between the GCC stock markets.

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